



HAL
open science

Assessing the Energy Impact of Cell Switch Off at an Urban Scale

Sekinat Yahya, Razvan Stanica

► **To cite this version:**

Sekinat Yahya, Razvan Stanica. Assessing the Energy Impact of Cell Switch Off at an Urban Scale. STWiMob 2024 - 17th International Workshop on Selected Topics in Wireless and Mobile Computing, Oct 2024, Paris, France. <hal-04767323>

HAL Id: hal-04767323

<https://hal.science/hal-04767323v1>

Submitted on 5 Nov 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY-NC-ND 4.0 - Attribution - Non-commercial use - No Derivative Works - International License

Assessing the Energy Impact of Cell Switch Off at an Urban Scale

Sekinat Yahya*, Razvan Stanica*

*Univ Lyon, INSA Lyon, Inria, CITI, EA3720, 69621 Villeurbanne, France
{firstname.lastname}@insa-lyon.fr

Abstract—Cell switch off (CSO) is a technique in the mobile networks sphere that has been proposed and implemented widely to achieve reduced energy consumption of base station (BS) deployments. The energy consumption of BSs has increasingly become an interesting research area and rightly so, given the advancement in modern networking technology and the increase in network resources demand. The aim of this work is to examine CSO closely by evaluating it over a real urban area in Europe and using real data from the mobile network deployment of a national European mobile network operator. Our aim is to quantify the energy impact of applying CSO techniques to real BS network deployments. Through a detailed modelling of the BS power consumption, we show that a total of 18 MW can be saved over the studied urban area in 24 hours within the purview of the defined quality of service constraints.

Index Terms—cell switch off, energy optimisation, mobile networks, energy consumption

I. INTRODUCTION

Energy optimisation research within the mobile networks community has gained traction in the last two decades due to the dire effects of climate change and social debates that ensued as a result of it. Moreover, the mobile traffic is projected to increase, with an expected number of 30.9 billion connected devices on the Internet by 2025 [1], a jump from the 10 billion units recorded in 2021. This underlines the need for mobile network solutions designed with energy efficiency in mind.

As a matter of fact, energy optimisation techniques have been applied to all parts of the mobile networks architecture [2], [3] and the general consensus is that the base station (BS) energy consumption is the most significant [4], hence the most worthy of immediate attention when it comes to control and optimisation solutions. Among these strategies focused on the radio access network (RAN), cell switch off (CSO) is considered to be effective for achieving BS energy efficiency (EE). Many studies have implemented this technique in various ways [5], some tackling the energy efficiency problem only, while others combine it with complementary BS operation issues.

In order to understand how a BS actually consumes energy, the commonly used base station power model is described by Auer *et al.* [4] and depicted in Fig. 1. In this figure, P_{out} represents the power consumed by the BS for user traffic transmission, with a maximum value of P_{max} , while P_{in} is the total BS power consumption. P_{idle} is the consumption of the BS in idle mode, not serving any user traffic, but not being switched off. In this state, although without serving any

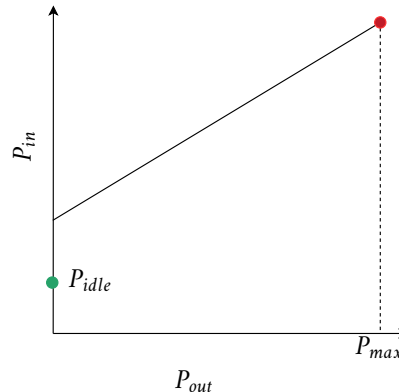


Fig. 1: Base station power consumption model.

user, the BS still consumes energy for transmissions on the broadcast and paging channels. With this model, it is easy to understand that BS functions that are not directly related to user traffic transmission significantly contribute to the BS power consumption. Therefore, CSO techniques are designed to target this significant consumption under low (or even zero) user traffic conditions.

The solutions proposed for CSO range from classical exact algorithms to custom heuristics and evolutionary techniques [5]. They can be classified into online and offline CSO [6]. The first class of solutions takes decisions in real-time, based on network measurements, while the second class consists of detecting patterns in historical data and planning a switch-off schedule. Online solutions are generally less complex, as they run in real time, while offline techniques are often presented as complex combinatorial optimisation problems.

However, these CSO settings are generally evaluated on small and regular cellular deployment scenarios, which are quite far from real network topologies. To overcome this, our study analyses the impact of CSO on a real BS deployment in a European urban area. For this, we use an offline CSO heuristic and evaluate the EE benefits it can bring, by varying several parameters in this scheme, to quantify their impact. Starting from the model in Fig. 1, we propose a modified BS power model that takes into account the proportion of traffic demand on the BS vis-à-vis its maximum traffic capacity. Using this model, we quantify the overall power gain achievable by applying CSO techniques to a real world scenario.

The remainder of this paper begins with a discussion of the related works in Sec. II. We proceed by presenting the system

model and the used CSO strategy in Sec. III. Results based on a real-world dataset are discussed in Sec. IV, before concluding remarks in Sec. V.

II. RELATED WORKS

The CSO problem is a complex combinatorial challenge which is NP-hard [7], [8]. This is due to the number of parameters that impact the CSO solution and to the complementary goals that can be targeted together with EE (e.g., throughput requirements, user association and mobility) [9]. Moreover, different mobile technologies have different requirements that need to be met for CSO to be implemented. For instance, CSO techniques implemented on 5G networks have different requirements to the ones used in 4G deployments, due to 5G specificities, such as the reduced coverage of millimetre wave BSs or the different traffic redistribution strategies [10].

Indeed, traffic redistribution, i.e. the method by which the traffic from the switched off BS is transferred to other cells so as not to compromise the quality of service (QoS) of the users, is a key component of the CSO technique. Regarding this aspect, some research indicates that it is better to transfer traffic from the switched off BS to other small cells nearby, rather than sending them to the macro base station in a heterogeneous network (HetNet) [11]. Also in a HetNet architecture, Nabuuma *et al.* [12] implemented a load-aware CSO technique which assumes maximum frequency reuse. It uses the allocation matrix when all the BSs are active and an estimate of the required sub-carriers by each BS to determine which one to switch off. Recently, some traffic redistribution techniques have been implemented using machine learning [13], [14].

Lately, CSO techniques take into account recent advances in wireless communications, such as Coordinated Multi-point Transmission (CoMP), Massive Multiple Input Multiple Out (M-MIMO) antennas, or Heterogeneous Cloud RAN (H-CRAN) [10]. Some techniques combine the goal of EE with other BS operations such as user association, traffic offloading, resource allocation and physical layer interference cancellation [11], [15].

In the design of CSO algorithms, there are often two possible states for the BSs in consideration, i.e. the *on* and *off* states. Hawasli *et al.* [16] implemented a CSO technique that gradually switches off BSs based on their location and densities. Other works have also implemented CSO techniques with sleeping modes in mind [10]. These techniques added two more states to the CSO, namely: *standby* and *sleep* states.

CSO can also be implemented sector-based [6]. Sector based CSO means that the sectors of a BSs can be switched off individually. The authors in [6] compared site-based and sector-based CSO algorithms vis-à-vis EE. However, switching off one sector out of three of a BS does not mean saving a third of the energy. The study concluded that focusing on the EE of the common equipment shared between sectors of the same site will achieve the reduced energy consumption desired. In some CSO techniques which consider spatial irregularity in the BS deployment, the switch-off criteria include a consideration of the spatial formulation of the remaining BSs after switch

off, i.e. in addition to EE, the objective will be to make the deployment as regular as possible [17], [18]. Most of these techniques are evaluated on contrived scenarios, considering small scale artificial deployments. Moreover, to the best of our knowledge, there is no consensus on what the order of magnitude of energy gains possible is, with the application of this technique on real base station deployments. To this end, our aim is to quantify the energy gain possible with implementing CSO at an urban scale within determinable QoS constraints.

III. SYSTEM MODEL

This section presents the system model and the CSO technique we adopted in this work. All the notations used in the remainder of the paper are summarized in Table I.

TABLE I: Notations

Symbols	Meaning
t	Time slot
τ	Total time duration
B	Set of BSs in the network
β_j	A given BS from set B
P_{off}	Off time percentage of all BSs in the network
α_0	Quality of service allowance
Ω	Maximum BS capacity
W	Redistribution traffic demand threshold
ω	Switch off traffic demand threshold
λ	Traffic redistribution radius
d_j	Traffic demand on β_j
Φ_t	BS switched off at time t
Ψ_j	Neighbours of β_j
$\lambda_{j,p}$	Distance between β_p in Ψ_j and β_j
Λ_j	Qualified neighbours of β_j
κ	Required number of qualified neighbours
P_j	Power consumed by β_j
P_t	Total power for all base stations at t
P_{soj}	Switch off power of β_t
P_{so_t}	Total power under CSO for all base stations at t
G_t	Power gain at current time t

A. BS Power Model

We consider a homogeneous network of BSs denoted as $B = \beta_1, \beta_2, \dots, \beta_n$. We observe this network for a time duration τ , divided in time slots denoted as t . The ultimate goal of a CSO algorithm is to reduce the BS network energy consumption. As discussed in Sec. I, CSO takes advantage of the BS power model proposed in [4] and based on Eq. (1):

$$P_{in} = P_{idle} + \Delta \cdot P_{out} \quad (1)$$

where P_{idle} is the power consumed by the BS at no load. This is the power consumed by the equipment required to keep the BS on, such as power amplifiers, AC-DC converters, active cooling, etc. It also includes the energy consumption required to regularly transmit information on the broadcast and paging channels, which are active even when no user traffic is transmitted in the RAN. P_{out} is the traffic dependent component of the BS power model. As more users are served, more physical resource blocks are used to carry information, hence consuming more energy. Fig. 1 provides a graphical representation of this model and Δ is the slope in this graph.

In our work, we modify this power model, as indicated in Eq. (2). This representation provides us with the power consumed by a BS as a function of its traffic demand:

$$P_j = P_{idle} + (d_j/\Omega) \cdot P_{max} \quad (2)$$

where P_j is the power consumed by a BS β_j , d_j is the traffic demand at the BS β_j , and Ω is the maximum traffic capacity of β_j . We calculate the total power consumed by the BSs at each time frame using this representation.

B. Traffic Redistribution

Algorithm 1 Switch Off

```

1: procedure SWITCH OFF DECISION
2:   for  $t \in \tau$  do
3:      $P_t = \text{sum}(P_j) \mid \text{apply Eq. (2)} : \forall \beta_j \text{ in } B$ 
4:     for  $\beta_j \in B$  do
5:       if  $d_j < \omega$  then
6:         get  $\Psi_j$  according to Eq. (3)
7:         redistribute = apply Algorithm 2
8:         if redistribute then
9:           | append  $\beta_j$  to  $\Phi_t$             $\triangleright$  Switch off  $\beta_j$ 
10:        end if
11:      end if
12:    end for
13:     $P_{so_t} = \text{sum}(P_{so_j}) \mid \text{apply Eq. (2)} : \forall \beta_j \text{ in } B$ 
14:     $G_t = P_t - P_{so_t}$             $\triangleright$  Power Saved
15:  end for
16:  return  $\Phi_t, G_t$ 
17: end procedure

```

The problem we want to tackle is twofold: BS switch off decision and redistribution of the switched off BS traffic to its neighbours. Indeed, a BS serving even a single user cannot be switched off if the user in question cannot be moved to a different BS without a significant impact on the perceived QoS. In our work, we use a heuristic solution for this joint problem. It is clear that the obtained result is not optimal, but we prefer such a heuristic, with parameters that are easy to identify and vary. The solutions used for BS switch off and traffic redistribution are shown in Algorithm 1 and Algorithm 2.

The two algorithms are linked: in order to be able to switch off a BS, we first need to manage to redistribute its traffic. First, we consider that, in order for a BS to be a candidate for switch off, its traffic demand needs to be relatively low. For this, we use a threshold ω (bit/s) at line 5 of Algorithm 1.

The second condition required to switch off a BS β_j is that the remaining cellular network needs to accommodate its traffic. To explain this process, we define Ψ_j as the neighbour base stations, situated within a radius λ of a given BS β_j , as illustrated by Fig. 2 and Eq. (3):

$$\Psi_j = \{\beta_p \mid \lambda_{j,p} < \lambda : \forall \beta \text{ in } \beta_t\} \quad (3)$$

where $\lambda_{j,p}$ represents the distance between β_j and β_p . In order to switch off β_j , its existing downlink and uplink traffic needs

Algorithm 2 Traffic Redistribution

```

1: procedure TRAFFIC REDISTRIBUTION ALGORITHM
2:   for  $\beta_p \in \Psi_j$  do
3:     if  $\beta_p \notin \Phi_t$  and  $d_p < W$  then
4:       | append  $\beta_p$  to  $\Lambda_j$ 
5:     end if
6:     if  $\text{size}(\Lambda_j) \geq \alpha$  then
7:       | for  $\beta_k \in \Lambda_j$  do
8:         | apply Eq. (5)
9:       | end for
10:      return True
11:     end if
12:   return False
13: end for
14: end procedure

```

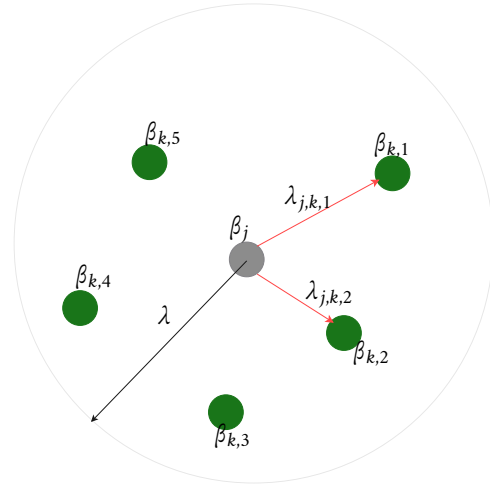


Fig. 2: β_j and its neighbours.

to be redistributed to these neighbouring BSs in Ψ_j . However, in our heuristic, two criteria need to be met by BSs in Ψ_j in order to accommodate this traffic. First, the neighbouring BS must not be switched off itself. For this, we define Φ_t as the set of BSs switched off at time t . Second, the neighbouring base station must not become overloaded when accepting the new traffic, as this would reduce the QoS of its existing users. For this, we use a threshold for the traffic demand, W , which represents the load limit for accepting traffic from a neighbouring BS. Practically, this means that a BS which already serves a traffic demand superior to W will not accept supplementary traffic from its neighbours. To this end, we define a subset of Ψ_j , which we denote by Λ_j and which represents the set of qualified neighbours for BS β_j . The set Λ_j includes all the neighbours that meet the two criteria above. Formally:

$$\Lambda_j = \{\beta_k \mid \beta_k \in \Psi_j, \beta_k \notin \Phi_t, d_k < W\} \quad (4)$$

where d_k represents the existing traffic demand served by β_k .

C. QoS Considerations

In our CSO solution, we consider that a BS can be switched off only if it has a certain number of qualified neighbours,

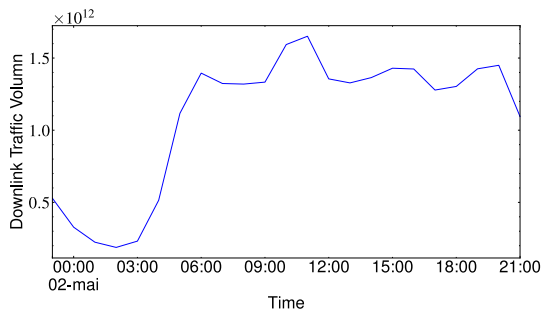


Fig. 3: Downlink traffic profile over a 24-hour period.

κ , to accommodate its traffic: $|\lambda_j| \geq \kappa$, as shown at Line 6 in Algorithm 2. This allows us to remain generic and not consider the precise locations of users associated with BS β_j in the decision process. If the traffic redistribution criteria are not met, the BS β_j will not be switched off. In the event that the switch off decision is taken, the traffic d_j of β_j is evenly divided between the qualified neighbors. However, the users previously served by β_j will now be served by a new BS, β_k , which is generally situated farther away from the users and provides a lower channel quality. To account for this, we consider that β_k needs to use more resources than β_j to provide the same level of QoS to the new users. For this, we use a parameter α_0 to increase the traffic demand at β_k , as follows:

$$d_{k+} = (\alpha_0 \cdot d_j) / |\lambda_j| \quad (5)$$

We note that, in our model, if the remaining BS are not able to provide the same QoS level to the users, we do not allow a BS to be switched off. This is a stricter requirement than many related works on CSO [5], where a certain user QoS degradation is allowed.

TABLE II: Reasons for not switching off a BS.

Notation	NSR
R1	BS has not enough geographical neighbours
R2	BS has too many neighbours already switched off
R3	BS has not enough qualified neighbours
R4	BS has a traffic demand superior to ω

Using this system model, we calculate the power consumed by the network before and after applying the CSO algorithm (see lines 5 and 15 of Algorithm 1). Regarding the BS that remained on, we divide the reasons of not switching off a BS into four categories, summarized in Table II: *i*) the BS does not have enough neighbours at a distance lower than λ , *ii*) too many neighbours of the BS are already switched off, *iii*) the neighbours of the BS do not have enough available capacity to accommodate the supplementary users, and *iv*) the BS has to serve a significant traffic demand.

IV. NUMERICAL EXAMPLE

We evaluate the CSO approach presented above using a real-world dataset, collected by a national mobile network operator in France. The data was collected from 172 4G

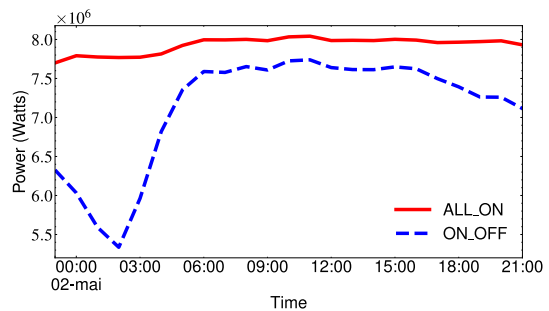


Fig. 4: Power consumption with and without CSO.

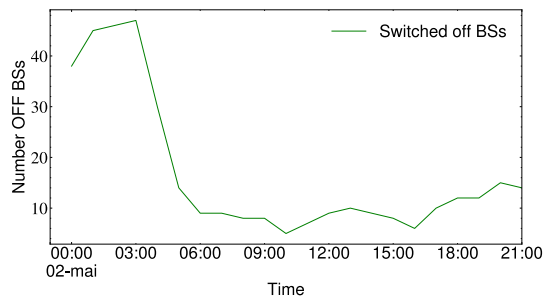


Fig. 5: Number of base stations switched off at each time t .

base stations deployed in the city of Lyon. Both uplink and downlink traffic information for these BSs is available, with a granularity of one minute. Our analysis focuses on a 24 hours period. The aggregated mobile traffic pattern in the city in this period is shown in Fig. 3. To obtain numerical results, we use the values indicated in Table III for the different parameters, unless explicitly indicated otherwise. The values for P_{max} and P_{idle} , which are the most important parameters in the BS power consumption model, were selected based on information provided in the literature [19], [20].

TABLE III: Parameters default values.

Parameter	Value
P_{max}	576 (W)
P_{idle}	750 (W)
Ω	$1.3 \cdot 10^9$ (bit/s)
λ	1000 (m)
κ	5
α_0	1.05
W	10^8 (bit/s)
ω	10^5 (bit/s)

We apply the CSO heuristic on the entire city of Lyon, based on the dataset described above. Fig. 4 shows the overall energy consumption of the network (i.e. all the BS), with and without CSO. The overall gain brought by the CSO technique over the entire day is in the order of tens of MW depending on the configuration of parameters in Table III. We notice that a significant gain is obtained during night hours, while the impact is reduced during the day. This is expected, considering that during the day the BSs are serving a higher user traffic demand, and they cannot be switched off without an impact on the user

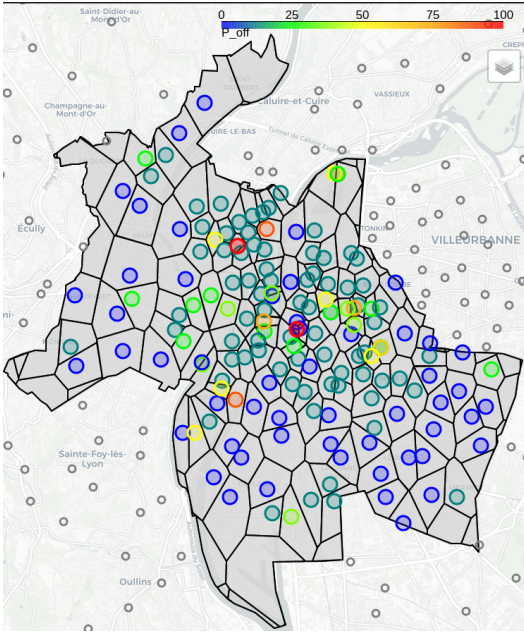


Fig. 6: Switch off frequency for different BSs.

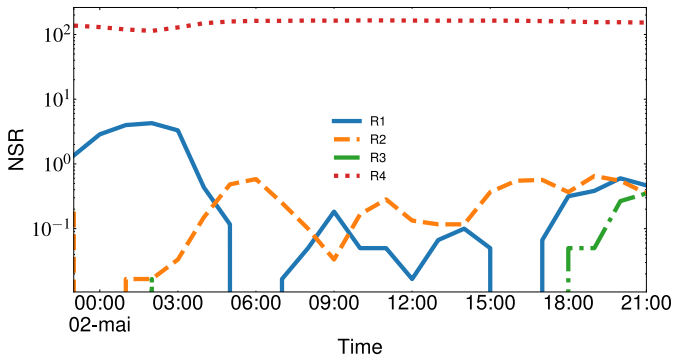


Fig. 7: NSR temporal evolution (please note the log y-axis).

QoS. This can also be observed in Fig. 5, where the number of switched off BSs is shown. Only a few base stations can be switched off over the entire city during the day. Fig. 6 shows the frequency of switch off (in %) of each BS in the city. Well over 100 out of the 172 BSs in the city are never switched off. The rest of the BSs are switched off to fairly even degrees, except for a few outliers, depicted in red in Fig. 6.

The temporal evolution of the non switch-off reasons (NSR), discussed in Table II, is shown in Fig.7. The main NSR, at any time of the day, is by far the fact that the BS are serving a quite consistent traffic load, which blocks their switch off (R4). The impact of the three other NSR varies during the day, with the geographical reason (R1) more important during the night, and the already switched-off neighbors (R2) representing a more significant NSR during the day.

The CSO heuristic we implement in this work presents a number of important parameters, which we vary to better understand their impact. Fig. 8 shows the impact of κ , the number of qualified neighbours required to switch off a BS. We

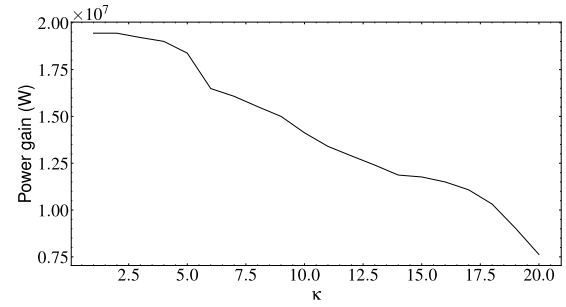


Fig. 8: Impact of κ on the power gain ($\lambda = 1000$, $\alpha_0 = 1.05$, $\omega = 10^5$, $W = 10^8$).

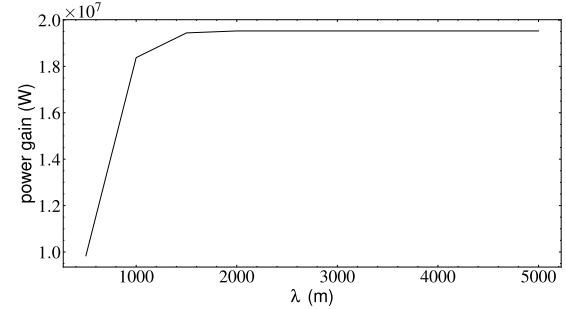


Fig. 9: Impact of λ on the power gain ($\kappa = 5$, $\alpha_0 = 1.05$, $\omega = 10^5$, $W = 10^8$).

observe that the power gain decreases as κ increases. Indeed, BSs situated in areas with a sparser deployment might have difficulties in finding a larger number of qualified neighbors.

In Fig 9, we observe a general upward trend in the behaviour of parameter λ , which represents the maximum radius of distance within which a BS may be considered as part of the neighbour of a BS β_j (see Fig. 2). This is due to the fact that, for lower values of this parameter, less BSs are switched off because it is generally harder for the relatively fewer neighbours of those BSs to meet the criteria for traffic redistribution.

We also observed the traffic thresholds ω and W in the same vein, in Fig. 10 and Fig. 11, respectively. We remark that the power gain increases with an increase in ω and W , before reaching some plateau values. This happens because increasing

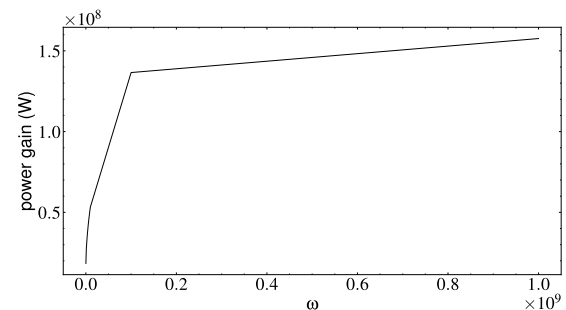


Fig. 10: Impact of ω on the power gain ($\kappa = 5$, $\lambda = 1000$, $W = 10^8$, $\alpha_0 = 1.05$).

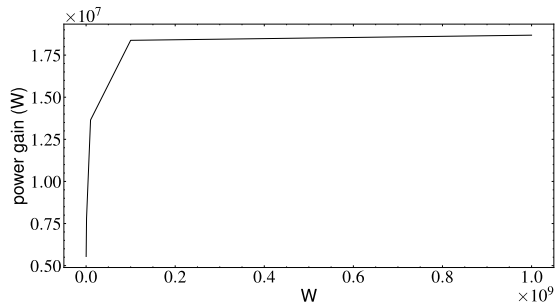


Fig. 11: Impact of W on the power gain ($\kappa = 5$, $\lambda = 1000$, $\omega = 10^5$, $\alpha_0 = 1.05$).

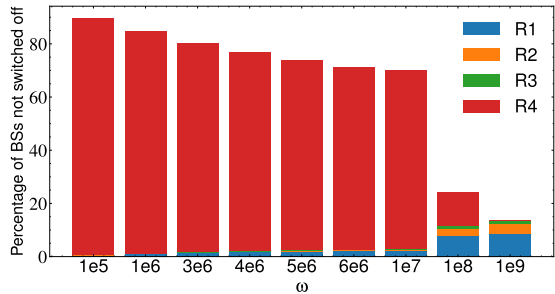


Fig. 12: Impact of ω on NSR ($\kappa = 5$, $\lambda = 1000$, $W = 10^8$, $\alpha_0 = 1.05$).

the thresholds changes the NSR, but the BS switch off is still blocked, for other reasons. We show this in Fig. 12, where we present the non switch-off reasons as we increase ω . We notice that, for values of $\omega < 10^7$, R4 (i.e. the BS traffic is higher than ω) is largely the most significant reason. As we increase ω from 10^5 to 10^7 , the number of BS blocked by R4 reduces, but it remains dominant. As we further increase ω , to 10^8 and 10^9 , a significant number of BS can be switched off, but other NSR appear, and the plateau observed in Fig. 10 is reached.

Finally, we evaluated the impact of α_0 , the QoS penalty parameter used in our model. The results are straightforward, and they do not require a dedicated figure: the achieved power gain decreases linearly, but very slowly, with the increase of α_0 . The overall power gain difference over 24h between $\alpha_0 = 1.02$ and $\alpha_0 = 1.1$ (meaning a QoS penalty between 2% and 10% of the user traffic demand) is less than 1 W. We therefore conclude that this parameter has a relatively reduced impact on the BS energy consumption.

To put these results in a broader context, we provide a brief comparative analysis. The average power consumed by an individual in the city of Lyon per day is 6 kW [21]. Using this number, the population of the city, and the market share of the operator in the city, we compute the daily energy gain of a mobile network subscriber from applying the CSO technique to be about 2%.

V. CONCLUSION

In this paper, we examined cell switch off, a popular technique used for energy optimisation in mobile base stations, by

evaluating the energy efficiency gain it brings over a real urban region using data from a mobile network operator. We evaluated all the important parameters of a CSO heuristic, including parameters related to QoS limitations, to better understand their impact. We report that CSO achieves a significant overall power gain of 18 MW during 24 hours and that our study quantifies (within reasonable constraints) the impact of CSO on a real cellular deployment.

REFERENCES

- [1] <https://www.statista.com/statistics/1101442/iot-number-of-connected-devices-worldwide/>
- [2] D. Lopez-Perez et al., "A Survey on 5G Radio Access Network Energy Efficiency: Massive MIMO, Lean Carrier Design, Sleep Modes, and Machine Learning", *IEEE Communications Surveys & Tutorials*, vol. 24, no. 1, pp. 653-697, January 2022.
- [3] A. Alnoman et al., "Energy Efficiency on Fully Cloudified Mobile Networks: Survey, Challenges, and Open Issues", *IEEE Communications Surveys & Tutorials*, vol. 20, no. 2, pp. 1271-1291, December 2018.
- [4] G. Auer et al., "How Much Energy is Needed to Run a Wireless Network?", *IEEE Wireless Communications*, vol. 18, no. 5, pp. 40-49, October 2011.
- [5] J. Wu et al., "Energy-Efficient Base-Station Sleep-Mode Techniques in Green Cellular Networks: A Survey", *IEEE Communications Surveys & Tutorials*, vol. 17, no. 2, pp. 803-826, February 2015.
- [6] T. Beitelmal et al., "Sector and Site Switch-off Regular Patterns for Energy Saving in Cellular Networks", *IEEE Transactions on Wireless Communications*, 17(5): 2932-2945, 2018.
- [7] E. Oh et al., "Dynamic Base Station Switching-On/Off Strategies for Green Cellular Networks", *IEEE Transactions on Wireless Communications*, 12(5): 2126-2136, 2013.
- [8] N. Yu et al., "Minimizing Energy Cost by Dynamic Switching On/Off Base Stations in Cellular Networks", *IEEE Transactions on Wireless Communications*, 15(11): 7457-7469, 2016.
- [9] G. Sun et al., "Energy Efficient Cell Management by Flow Scheduling in Ultra Dense Networks", *KSI Transactions on Internet and Information Systems*, 10(9): 4108-4122, 2016.
- [10] M. Feng et al., "Base Station On-Off Switching in 5G Wireless Networks: Approaches and Challenges", *IEEE Wireless Communications*, 24(4): 46-54, 2017.
- [11] R. Tao et al., "An Energy Saving Small Cell Sleeping Mechanism with Cell Range Expansion in Heterogeneous Networks", *IEEE Transactions on Wireless Communications*, 18(5): 2451-2463, 2019.
- [12] H. Nabuuma et al., "A Load-Aware Base Station Switch-Off Technique for Enhanced Energy Efficiency and Relatively Identical Outage Probability", *Proc. IEEE VTC Spring*, 2015.
- [13] M. Hoffmann et al., "A Reinforcement Learning Approach for Base Station On/Off Switching in Heterogeneous M-MIMO Networks," *Proc. IEEE WoWMoM, Cork, Ireland*, 2020, pp. 170-172.
- [14] I. Guerra et al., "Optimization of Base Station ON-Off Switching with a Machine Learning Approach," *Proc. IEEE ICC, Montreal, QC, Canada*, 2021, pp. 1-6.
- [15] M. Feng et al., "BOOST: Base Station On-Off Switching Strategy for Energy Efficient Massive MIMO HetNets", *Proc. IEEE INFOCOM*, 2016.
- [16] M. Hawasli and S.A. Colak. "Toward Green 5G Heterogeneous Small-Cell Networks: Power Optimization using Load Balancing Technique", *AEU-International Journal of Electronics and Communications*, 82: 474-485, 2017.
- [17] Q.-N. Le-The et al., "Cell Switch-Off Algorithms for Spatially Irregular Base Station Deployments", *IEEE Wireless Communications Letters*, 6(3): 354-357, 2017.
- [18] F. Lagum et al., "Cell Switch-Off for Networks Deployed with Variable Spatial Regularity", *IEEE Wireless Communications Letters*, 6(2): 234-237, 2017.
- [19] C. Desset et al., "Flexible Power Modeling of LTE Base Stations", *Proc. IEEE WCNC*, 2012.
- [20] H. Holtkamp et al., "On Minimizing Base Station Power Consumption", *Proc. IEEE VTC Fall*, 2011.
- [21] Consommation électrique moyenne d'un ménage français en 2023 (2022) Fournisseurs. Available at: <https://www.fournisseurs-electricite.com/guides/consommation/consommation-electrique-moyenne> (Accessed: February 1, 2023).